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Regionalisation of a PDM Model for Catchment Runoff in a Mountainous region of Korea

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Abstract

This study aims to regionalize a rainfall-runoff model within the mountainous Geum River catchment, Korea. A version of the Probability Distributed Moisture model is applied to 19 gauged sub-catchments. A Monte Carlo based method is used for the calibration and validation of the model using three objective functions targeting overall performance, as well as low and high flow regimes specifically. A set of multivariate regression models linking model parameters and catchment characteristics is developed. The regionalised and locally calibrated models are compared using the leave-one-out cross-validation method. The validation results show that the regionalised model has equal or better performance than the locally calibrated model at 12 (for high flow model), 10 (for low flow model) and 10 catchments (for overall flow regime model) respectively. This study shows the potential of the regionalisation of the Probability Distributed Moisture model within the Geum River region. The results show that the suggested regionalized models for high and low flow regimes are better than a single model for the overall flow regime model. It is expected that this approach can usefully support water resource management in comparable ungauged mountainous, monsoon-affected catchments.

Keywords: rainfall runoff model, ungauged catchment, regionalisation, Korean catchments

1 Introduction

Weather-related natural disasters such as typhoons, droughts and floods are common in East Asia and on the Korean Peninsula, and the resulting economic damages are rapidly increasing as the society has developed (www.safekorea.go.kr). Development and implementation of effective flood and drought mitigation strategies requires better understanding of hydrological processes at the catchment scale. Korea is heavily influenced by Monsoon precipitation in summer (June-September), with approximately 70% of annual precipitation occurring in that period, not too dissimilar to climate patterns observed in arid and semi-arid regions. The combination of prolonged dry periods combined with short periods of extreme precipitation is a challenge to replicate in parameter parsimonious rainfall-runoff models. Hydrological observation has a long history in Korea, and important sections of major rivers, such as Han River, Nakdong River and Geum River, have been gauged since 1916 (www.kma.go.kr). However, most of the small to medium-sized catchments in Korea do not have enough observed hydrological data to support flood and drought mitigation planning and many of them are completely ungauged (Choi et al., 2010).

Prediction of streamflow in ungauged catchments has been a challenging task for hydrologists. Globally, many studies have estimated and other hydrological responses in ungauged catchments. In the last decade (2003-2012), Prediction in Ungauged Basin (PUB) was the main research theme of the International Association of Hydrological Sciences (IAHS). Parajka et al. (2013) and Salinas et al. (2013) summarize the major results of the PUB of the IAHS. Parajka et al. (2013) present a comparative assessment, with meta-analysis of 34 published studies involving 3874 catchments. This included comparing performances of the following approaches to regionalisation: regression of model parameters against catchment characteristics (CCs); transferring a model and its parameter sets from one or more similar or nearby catchments; calibrating a model, including any relationships between model parameters and CCs, simultaneously over many catchments in a region; and averaging model parameters over sets of similar catchments. They found that in general: predictions are more accurate in humid and cold regions than in arid regions; more accurate in large than in small catchments; more accurate in studies with either a large or small (rather than intermediate) number of gauges; and that regression when compared with other methods tends to perform worse, although this depends on climate and on number of gauges available. Meanwhile, the meta-analysis of Salinas et al. (2013), which is based on 14 low flow studies involving 3122 catchments and 20 flood studies involving 3023 catchments, concludes that both flood and low flow predictions in ungauged catchments are more accurate in humid than in arid catchments. The inter-comparison studies are inconclusive about recommending approaches. The regression approach has the principal attraction of being able to interpolate model parameter values between CCs, therefore not necessarily relying on the CC space being densely sampled by the gauged catchments. However, it has the theoretical disadvantage over the model transfer approach that parameter inter-dependencies inherent to calibration results are either neglected or greatly simplified in the regression, potentially increasing uncertainty in the regression and lowering performance (McIntyre et al. 2005). Furthermore, the simplified nature of the models means that the physical significance of parameters is often ambiguous and variable over a large sample of catchments, and so the parameters are unlikely to have strong relations with CCs (Moore et al. 2006). Despite these issues, regression is the most established approach especially in flood studies.

There have been a number of regionalisation studies in East Asia, where catchments tend to be steep, and runoff responses affected by highly seasonal, Monsoon-affected climate and occasional typhoons. Yokoo et al. (2001) suggested a parameter regionalisation of the Tank Model (Sugawara, 1961) by using 12 catchments in Japan. The authors considered the regionalization to produce acceptable

model performances at ungauged catchments. Lee and Kang (2007) and Kang et al. (2013) regionalised the Tank Model in Korea. Kang et al. (2013) estimated regression equations for eight model parameters while fixing three model parameters. This provided acceptable hydrograph simulations (r^2 , the coefficient of determination, greater than 0.88), although the peak flows were underestimated. Semi distributed models have also been used to model runoff in ungauged catchments in the region. For example, Lee et al. (2009) successfully applied the semi-distributed SWAT model (Neitsch et al., 2001) for regionalisation of rainfall runoff model, and to estimate stream flow in Soyang, Chungju and Daecheong catchments. Choi et al. (2010) used a spatially distributed model (GRM, Choi et al., 2008) to estimate parameters for upstream ungauged catchment by calibrating at downstream gauges, which was considered successful for two well gauged Korean catchments. Although these studies have begun to expose the challenges and potential for regionalization in East Asian, Monsoon dominated, mountainous areas, there is a lack of evidence in the literature about the suitability of the different approaches in such areas, particularly regarding specific focus on high and low flow regimes (Kim et al., 2014).

The objective of this study is to test a regionalisation model for Korean catchments including investigating its performance for specific flow regimes: overall, high and low flows. The regionalisation is developed and assessed using 19 well gauged catchments in the Geum River region, Korea.

2. Study catchments, Geum River region

2.1 Description of Geum River

The Geum River is one of the major rivers in Korea, draining the mid-western region of the Korean peninsula. The Geum River region has a temperate climate with four distinct seasons, and the average annual temperature and precipitation in this region are 11.5°C and 1285mm respectively (www.wamis.go.kr). In summer, the East Asian Monsoon brings heavy precipitation to Korea; approximately 70% of precipitation occurs from June to September, which is a general feature of Korean catchments (MLTM, 2011; MLTM, 2016). For the Geum River region, hydro-meteorological and catchment characteristic (CC) data are available for 19 gauged catchments. The quality of hydrological data, including field observations and development of stage-discharge curves, has been improved since The Hydrological Survey Center (www.hsc.re.kr) was established as a national agency in 2007.

The locations of the catchments are shown in Figure 1. Land use is dominated by natural woodlands and agriculture. The Government officers of the Geum River Flood Control Office provided individual comments on selection of the study catchments (MLTM, 2016). The flow gauges located downstream of the Daecheong Multipurpose Dam (D1) and Geum River estuary barrier (D3) are excluded from the regionalization because of the non-natural flow regime.

Figure 1. Study catchments in Geum River region, Korea

2.2 Data

The hydro-meteorological data (i.e., flow, precipitation and other climatic data) were obtained from the Water Resources Management Information System (WAMIS, www.wamis.go.kr). The temperature

and precipitation data were provided by the Korea Meteorological Agency and the potential evapotranspiration values were estimated by using the Penman-Monteith formula developed by the Food and Agriculture Organization of the United Nations (Kim, 2010).

Daily average hydro-meteorological data for the period of 2001-2015 were prepared for each of the 19 catchments. The calibration and validation periods, common across all catchments, were selected as 2006 to 2015 and 2001 to 2005 respectively. The years in which flow data were missing or considered to be of doubtful quality, shown in Table 1, are excluded from the calibration and validation data sets.

Table 1. Years of missing & erroneous flow observations

The CCs are a set of indicators describing the physical features of each catchment. Eight CCs were selected based on a previous assessment of hydrologically important CCs (Ko, 2012). These CCs are considered to describe the key aspects of the geographical and climatological features of the region as discussed in Section 2. The eight CCs are: catchment area, *A* (km²); the mean catchment altitude, *ALTBAR* (m); drainage density, *DD* (-); the form factor, *FF* (-); the Curve Number, *CN2007* (-); an index of flood attenuation, *FARL* (-); Drainage Path Slope of the catchment, *DPS* (°); and Standard Annual Average Rainfall for the period of 1981 to 2010, *SAAR* (mm).

A is the size of the catchment, which may affect the lag and dispersion of hydrographs as well as spatial variability of runoff generation. *ALTBAR* is the average altitude of catchment above sea level. *ALTBAR* and *DPS* affects the surface runoff response time. *DD* is the measure of the total length of all the rivers in a catchment area divided by the total area of the catchment. *It* represents how well (or how poorly) a catchment is drained by stream channels. *FF* is the ratio of the catchment area to the squared value of the catchment length, varying from near 0 (in highly elongated catchments) to near 1 (in circular shaped catchments). *CN2007* is the SCS-CN number developed by the US Soil Conservation System (SCS), which reflects the volume of runoff associated with soil type, land use and a precipitation event (Hong and Alder, 2008). *FARL* is an index measuring flood attenuation effects by upstream lakes and reservoirs (Bayliss al., 1999) and is estimated based on the reservoir data and the catchment terrain database in *Water Resources Management Information System (WAMIS)* in Korea. *DPS* is the mean of the catchment slope. *SAAR* is estimated using the average annual precipitation data for the past 30 years. The values of these eight CCs are shown in Table 2.

Table 2. The CCs of 19 catchments at Geum River Region, Korea

3. Rainfall Runoff model and calibration

A version of the *Probability Distributed Moisture model (PDM)*, developed by Moore (1985, 2007), is used in this study. The PDM is a lumped conceptual rainfall runoff model, and is widely used in hydrological analysis in United Kingdom (Kay et al., 2007) and Korea (Ahn et al., 2009; Chang and Lee, 2015). This study applied a version of the PDM as implemented in the Runoff Rainfall Modeling Toolkit (Wagener et al., 2004). Details of the PDM model structures and applications are described in Moore (2007) and only a brief summary is provided here.

3.1 Probability Distributed Model (PDM)

The schematic diagram of the PDM model is shown in Figure 2, Tables 3 and 4 list the parameters of the PDM model and the assumed plausible ranges of values; and summaries of the runoff production and flow routing components of the model are provided below.

3.1.1 Runoff production

Moore (2007) represented the spatial distribution of soil moisture capacity in a catchment as a Pareto cumulative distribution function, $F(c)$:

$$F(c) = 1 - \left(1 - \frac{c}{c_{max}}\right)^b, 0 \leq c \leq c_{max} \quad (1)$$

The soil moisture storage component of the model has two parameters, c_{max} and b . The parameter c_{max} represents the maximum soil moisture capacity in the catchment, and c is a variable representing the soil moisture capacity. The distribution function is implemented in the modelling as follows. The catchment-average soil moisture storage capacity (S_{max}) is calculated from equation 2, the actual catchment-average storage (S_k) from equation 3, and then the actual maximum storage in the catchment (c_k) from equation 4.

$$S_{max} = \frac{c_{max}}{(b+1)} \quad (2)$$

$$S_k = S_{max} \left[1 - \left(1 - \frac{c_k}{c_{max}}\right)^{(b+1)}\right] \quad (3)$$

$$c_k = c_{max} \left[1 - \left(1 - \frac{S_k}{S_{max}}\right)^{\frac{1}{(b+1)}}\right] \quad (4)$$

Equation 5 shows the calculation of the effective rainfall (ER_k) generated at time step k . It is based on the fill and overflow concept, whereby if precipitation causes the soil storage capacity at any point in the range $0 - c_{max}$ to be exceeded, effective rainfall is generated at that point

$$ER_k = \max[r_k - ae_k - (S_k - S_{k-1}), 0] \quad (5)$$

Where, r_k is the rainfall. ae_k is the actual evapotranspiration, which is the adjusted potential evapotranspiration based on catchment wetness in equation 6.

$$ae_k = \frac{S_k}{S_{max}} pe_k \quad (6)$$

The parameter b controls the spatial variation of the soil moisture capacity of the catchment. If b is equal to 1, then the soil moisture storage is uniformly distributed in the catchment, and as b tends towards 0, the soil moisture storage capacity tends towards a single value of c_{max} .

3.1.2. Flow routing

Two linear, parallel reservoirs are used to route the effective rainfall to the catchment outlet, as shown

in Figure 2. The nonlinearity between rainfall and runoff responses could be accounted in the runoff production (i.e. the soil moisture model). Therefore, the remaining routing could be approximated by a linear relationship (Jakeman and Hornberger, 1993). The two linear reservoirs represent the quick and slow responses of the catchment respectively. A proportion, $\% (q)$, of the effective rainfall contributes to the quick response reservoir, while $1 - \% (q)$ contributes to the slow response reservoir. The flow response of each reservoir is defined by Eq. (7). The time constants of quick and slow reservoirs are rtq and rts respectively.

$$\frac{dQ_q}{dt} = \frac{1}{rtq} [\% (q) \cdot ER_k(t) - Q_q(t)] \quad (7a)$$

$$\frac{dQ_s}{dt} = \frac{1}{rts} [(1 - \% (q)) \cdot ER_k(t) - Q_s(t)] \quad (7b)$$

Figure 2. Schematic diagram of PDM

(where, r_k : rainfall, ae_k : actual evapotranspiration, C_{max} : maximum soil moisture capacity, b : spatial variation of the soil moisture capacity, S_k : soil moisture storage, C_k : soil moisture capacity, ER_k : Effective rainfall, $\% (q)$: volume of fast reservoir in effective rainfall, rtq : time constant for fast reservoir, rts : time constant for slow reservoir, Q : streamflow)

Table 3. Parameters of Probability Distributed Moisture Model

3.2 Calibration and validation

The PDM model is calibrated and validated using the Monte Carlo Analysis Toolkit (MCAT) (Wagener and Kollat, 2007). The MCAT is based on a Monte-Carlo method which is conceptually simple and easy to apply, and widely used in modeling practice (Choi and Lee, 2012). A large number of parameter sets are generated using uniform random sampling from the parameters' prior ranges, the model is run using each sample, and an objective function (OF) is calculated that quantifies model performance with respect to the flow observations. The parameter identifiability and uncertainty is then assessed by response surface and sensitivity analysis (Beven, 2001).

10,000 parameter sets were sampled from the ranges given in Table 3. Three OFs are used to measure high flow, low flow and overall flow aspects of model performance: (i) RMSE-HF (Root Mean Square Error for High Flows) where high flow is greater than $1.25 \times$ mean flow for that gauge; (ii) RMSE-LF (Root Mean Square Error for Low Flows), where low flow is smaller than $0.25 \times$ mean flow; and (iii) The complement of Nash Sutcliffe Efficiency ($NSE^* = 1 - NSE$) applied to all flow values (Nash and Sutcliffe, 1970). The RMSE-HF and RMSE-LF have units mm/day while the NSE^* is unitless. For all three, a value close to zero indicates good performance. The NSE^* and RMSE are defined by Equations (8) and (9).

The model performance obtained from the optimum sampled parameter set for each OF and each catchment was visually inspected by considering the difference between the simulated and the observed hydrographs for and quantitatively evaluated using the OF values, in both calibration and validation periods. The first 20% of these periods was used as a warm-up period, included in the simulation but omitted when calculating the OF values.

$$NSE^* = \frac{\sum_{i=1}^n (o_i - s_i(\theta))^2}{\sum_{i=1}^n (o_i - \bar{o})^2} \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (o_i - s_i(\theta))^2} \quad (9)$$

(where, o_i is observed flow at time i , \bar{o} is mean of observed flow, $s_i(\theta)$ is simulated flow at time i with parameter set θ)

3.3 Regionalisation

Multiple linear regression equations are developed to enable prediction of the PDM model parameters in ungauged catchments. A linear least-squares regression analysis is developed for each of the five PDM parameters, using the optimal (calibration) parameter values from the gauged catchments for a selected OF and the corresponding sets of CCs. CCs to be included in the final regression equation were selected based on the backward elimination method (p-value is less than 0.1) as implemented in the Statistical Package for the Social Sciences (SPSS) software. The final regression equation identified by that method has a better p-value than all previous equations. Three final regression equations are developed, one for each OF.

3.4 Performance assessment of regionalisation

The regression models are assessed using a leave-one-out cross validation technique (Miller, 1974). This approach is briefly explained here and Joo et al. (2014) provides a more detailed explanation. The technique aims to overcome the paucity of available data by more efficiently using the entire data set for the validation. The method works by first identifying the significant CCs using all N catchments as explained in the preceding sections. Then one 'test' catchment is removed and the regression equation coefficients are estimated using the other ($N-1$) catchments. The resulting regression equations are used to predict the parameter values for the test catchment and to simulate its flow time series in the validation period and calculate its OF values. Each of the N catchments is in turn used as the test catchment so that N sets of regression equations are developed and validated.

4 Results

4.1 Application of the PDM model

The application of the model is explained using the example of the C5 (Cheongseong) catchment. Figure 3 shows the input time series of the daily hydrological data (precipitation, runoff, and potential evapotranspiration) for the period from 2006 to 2015. The strong seasonal differences in precipitation, evaporation and runoff are evident, with the bulk of the runoff occurring during the relatively short wet summer period. Also, the flashy nature of the runoff response is evident, with several orders of magnitude difference between runoff recorded during the wet and dry seasons.

Figure 3. The rainfall, runoff, potential evapotranspiration data at gauge C5 (Cheongseong) (1 Jan 2006 to 31 Dec 2015)

Figure 4 a), b) and c) show calibrated hydrographs of the PDM model for each OF at catchment C5. The calibrated hydrographs of the NSE* and RMSE-HF are considered acceptable in comparison with the observed hydrographs overall. However, the extreme peaks of the hydrograph are underestimated. The results of the RMSE- LF show that the low flow part of the hydrograph is acceptably simulated. The high flows are significantly underestimated; however, these flows are not considered in calculation of RMSE-LF.

Figure 4. Observed and simulated hydrographs in the calibration period (1 Jan 2011 to 31 Dec 2015) and validation period (1 Jan 2001 to 31 Dec 2003) at gauge C5; (a) RMSE- HF = 6.2 mm/day, RMSE- LF = 0.12 mm/day and NSE* = 0.25, (b) RMSE-HF = 7.73 mm/day, RMSE-LF = 0.16 mm/day, NSE* = 0.33

NSE* is a type of generalized performances measure, which able to compare its performance over the catchments. RMSE is useful to examine the performances with its magnitude of flow, for especially high and low flow regimes. Tables 4, 5 and 6 show the calibrated parameter values and the calibration and validation OF values for RMSE-HF, RMSE-LF and NSE*. For RMSE-HF, Table 4 shows that C_{max} has a low variation across catchments (216-487 mm) relative to the prior range used, while b varies widely (0.3-2.4). The rtq has a relatively constant, low value (1.0-2.4 days); furthermore the $\% (q)$ stays relatively close to 1.0 (0.47-0.99), showing that the flashiness of these catchments must be captured by the model to replicate high flows. Conversely, rts has a wide variation (55-438 days) because it has little influence on the high flow objective function especially given the low volumes of simulated baseflow.

Table 5 shows that the parameter sets identified using RMSE-LF are widely different to those identified using RMSE-HF. The most important difference is the relatively small $\% (q)$ values, representing the increased importance of accurately modelling the flows through the slow store.

Table 6 shows the NSE* results, which are considered acceptable ($NSE^* < 0.6$) for all catchments in calibration and for 15 catchments in validation. The poor validation results are shown with (), and these are not considered in further analysis. C_{max} shows a wide variation (128-500 mm). b also varies widely (0.1-1.8); however most values are less than 1.0. rtq has relatively constant values (1.1-2.4 days) and $\% (q)$ values are relatively close to 1.0 (0.46-0.99), showing that the flashiness of these catchments must be captured by the model to replicate high flows. rts has a wide variation (76 – 480 days), similar to the distribution obtained using RMSE-HF. This is because neither of these OFs is designed to extract information about the low flow response parameters.

Table 4. Calibration and validation period results using RMSE-HF

Table 5. Calibration and validation period results using RMSE-LF

Table 6. Calibration and validation period results using NSE*

4.2 Regression equations

Table 7 shows the regression equations for each MP developed for individual OFs. The R^2 -value and p-values of equations show a wide variation from 0.14 to 0.98 and from 0.01 to 0.41 respectively. The R^2 values of regression equations for RMSE-HF and RMSE-LF are consistently higher than those of NSE*, except rts. Although the statistical significance of some regression equations (i.e., rts for RMSE-HF and RMSE-LF, and rtq for NSE*) are very low, It shows that the focusing on specific flow regimes improves the statistical significance of regression equations. The results of rts indicate that the slow response of the catchment is the long term interaction between subsurface and groundwater. It is not fully captured in short term flow segmentations.

For the other parameters, the regression equations contain useful information about the hydrological processes (in terms of CCs) controlling runoff. For example, $\%(q)$ (Percentage flow through quick flow) has a negative relationship with A(Area) and CN2007 (SCS-Curve Number) in the RMSE-FH, RMSE-LF and NSE*. It follows a hydrological understanding of Korean catchments, such as; the large natural catchments have relatively slow flow responses. The results for some model parameters (such as b for NSE*) are difficult to interpret in terms of the physical influence of CCs despite the p value being low.

Table 7. Regionalisation models considering parameters and characteristics at Geum River catchments by OFs

4.3 Leave-one-out cross-validation of regionalised model

A leave-one-out cross-validation was undertaken for the 15 catchments. The selected CCs for each MP are kept constant at those in Table 7 so that only the coefficients were different for each of the 15 catchments. The other 4 catchments, which were not used to develop the regression result in Table 7, were also used as validation catchments. The performances of the regionalized model are shown in Table 8 and are compared with the locally calibrated model performances in Figure 5 Both sets of performances are for the same validation period (1 Jan 2001 to 31 Dec 2005).

Table 8. Leave-one-out cross-validation results of the regionalised model parameters

The RMSE-HF results in Figure 5 (a) are located near the 45 degree line, with less than 10% difference between the validation and regionalization performances for 18 catchments. This shows that the regionalisation is almost as good as validation when focusing on performance in the high flow

part in the hydrograph. The RMSE-LF results in Figure 5 (b) show that there is less than 10% difference between the validation and regionalization performances for 7 catchments; while the NSE* results show that there is less than 10% difference between the validation and regionalization performances for 14 catchments. It may be concluded that regionalization of the PDM model for predicting high flows is relatively successful, but there are increasing challenges for predicting the low and medium flows.

Figure 5. Comparison of model performance between using calibrated (Cal) model parameters and using regionalised (Reg) model parameters

Figure 6 shows the regionalised model performance in terms of RMSE-HF and RMSE-LF in validation period, when the NSE-optimal parameters are used for regression. The y axes are the resulting RMSE-FH and RMSE-LF values, while the X axes are the equivalent performances but when using the RMSE-HF and RMSE-LF optimal parameter sets for the regression. Figure 6 (a) indicates that there is no benefit in using RMSE-HF instead of NSE* when targeting high flow performance at ungauged basins; while Figure 6(b) shows that in most cases there is a benefit in using RMSE-LF when targeting low flows. Despite the large uncertainties involved in the regionalisation, there remains a clear benefit in using separate models for high flow and low flow applications.

Figure 6. Comparison of: a) RMSE-HF validation performance when using NSE* and RMSE-HF optimal parameter sets to derive the regression equation; b) RMSE-LF validation performance when using NSE* and RMSE-HF optimal parameter sets to derive the regression equation

C5 (Cheongseong) is used as an example to provide further insight into regionalisation performance. Table 9 gives the regionalised model parameters and validation results. The regionalised parameter values are sensible compared to the calibrated values in Tables 4, 5 and 6. Figure 7 shows the regionalized hydrographs. The hydrograph for C5 represents most of the observed stream flows except the extreme peak flows.

Table 9. Summary of regionalisation results for C5 catchment

Figure 7. Hydrographs of regionalised models based on leave-one-out cross-validation at C5 catchment

The improvement of the regression equations based on high flow regime (RMSE-LF) is visually marginal comparing to the results of all flow regime (NSE*). However, the results of low flow regime show improved results

1 comparing to those of using whole flow regime, NSE*. It confirms that distinguishing between low and high flow
2 regimes are important in improving in prediction of stream flow at ungauged catchments.

5. Conclusions

6 This study aims to develop a regionalisation of the PDM model for the Geum River catchments, Korea.
7 A version of the PDM model is applied to 19 catchments with observed daily hydrological data from
8 2001 to 2016. The Monte Carlo method is used for the calibration and validation using NSE*, high
9 flow (RMSE-HF) and low flow (RMSE-LF) objective functions. The main outcomes are:

10 - Multiple linear regression models are identified that allow PDM model parameters to be estimated
11 from available CCs at ungauged Korean catchments.

12
13 - A leave-one-out cross-validation shows that the regionalisation achieves a model performance
14 similar to that achieved by a locally calibrated model. The results show that the regionalised model is
15 at least as good as the locally calibrated model at more than 50 % of the tested catchments. The
16 results also show that using flow data specific to high and low flow applications, is essential for the
17 regionalisation.

18
19 This study shows the potential of regionalizing the PDM model in the Geum River region and is
20 expected to be a useful approach for supporting water resource management in the ungauged
21 catchments of Korea.

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